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THESIS

A MODEL FOR PREDICTING THE REPAIR COSTS OF U.S. NAVY INVENTORY ITEMS

by

Chunwei TAN, Jeffrey

December 2003

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13. ABSTRACT (maximum 200 words)

This research was initiated due to a report claiming that The U.S. Navy significantly overestimated repair prices in a Performance Based Logistics (PBL) reward to a contractor. The purpose of this thesis is to develop a model for improving the prediction of repair price for U.S. Navy inventory items.

The thesis examines several prediction methodologies, including a ratio-estimator prediction method that is a modification of the methodology currently in use, as well as regression analysis. In contrast to the ratio-estimator approach, regression is able to utilize a wide range of predictor variables, several of which are evaluated in the thesis research. Results of this analysis reveal that a regression model with logarithmic transformations yields more accurate predictions of repair prices than the current methodology. This improvement is seen especially for items that have the highest replacement price.

One feature of the proposed regression-based methodology is that predicted repair prices for the most expensive items are substantially lower than with the current methodology. In the case where that prompted the thesis research, the overstatement of benefit from the PBL would have been reduced by about 30 million under the proposed methodology.

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A MODEL FOR PREDICTING THE REPAIR COSTS OF U.S. NAVY INVENTORY ITEMS

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Submitted in partial fulfillment of the requirements for the degree of

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The thesis examines several prediction methodologies, including a ratio-estimator prediction method that is a modification of the methodology currently in use, as well as regression analysis. In contrast to the ratio-estimator approach, regression is able to utilize a wide range of predictor variables, several of which are evaluated in the thesis research. Results of this analysis reveal that a regression model with logarithmic transformations yields more accurate predictions of repair prices than the current methodology. This improvement is seen especially for items that have the highest replacement price.

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EXECUTIVE SUMMARY

The U.S. Navy has initiated programs to team with private industry for logistics support. In particular, Performance Based Logistics (PBL) initiatives have been undertaken by Naval Inventory Control Point (NAVICP)-Philadelphia to achieve its goals for improving support and lowering total ownership cost of the Naval inventory items under its management. For each PBL initiative, NAVICP conducts a business case analysis (BCA) to estimate its cost benefits in order to support the decision to award the contract.

This research was initiated as a result of a report by the Department of Defense Office of the Inspector General (DoD IG) claiming that NAVICP overstated cost saving in the F/A-18E/F Integrated Readiness Support Teaming (FIRST) Program award to Boeing. The report found that the cost of repairs conducted by Boeing were substantially lower than what the Navy paid for these repairs, based on its repair-price estimates. Estimated repair prices in NAVICP's BCA analysis were more than two hundred percent higher than the actual repair price reported by Boeing. Most of the discrepancy was attributed to repairable items that had the highest replacement price ($10,000 and above).

The thesis research examined alternative methodologies for predicting repair prices with the aim of improving the prediction accuracy of the methodology currently used by NAVICP. The current methodology uses ratio estimators for a categorization of repairable items based on their replacement price. Within each of six replacement price categories, the average of the ratios of repair price to

replacement price is calculated, using equal weighting. For an item with no historical repair-price data, its repair price is predicted by multiplying the appropriate ratio by its replacement price.

A modification of the ratio methodology was considered, which weighted the averages proportionally to the replacement prices of items within a category. Analysis using the modified ratio methodology offered slightly improved results for items in the highest replacement price category. However, an analysis of both ratio methods found that replacement price alone is not a strong predictor of repair price.

An investigation was then made into the use of regression models for the prediction of repair prices. These models considered variable transformations as well as additional predictor variables. The simplest regression model used the logarithm of replacement price to predict the logarithm of the ratio of repair price to replacement price. More extensive regression models included categorical predictor variables based on the Federal Stock Class (FSC) and Local Routing Code (LRC) of an inventory item. Stepwise regression procedures were used to identify models that had good predictive power without overfitting.

Regression models that included combined categorical groupings of FSC and LRC yielded the best prediction power. However, the level of improvement was small when compared to the simple regression model that used only the logarithm of replacement price as a predictor.

The prediction methodologies that were analyzed were then evaluated on the repair data cited in DoD IG’s report

on the FIRST program. The simplest regression model resulted in a substantial improvement over the current methodology for the inventory items that were considered. The total prediction error was reduced from forty-seven million dollars (current methodology) to fourteen million dollars (regression).

The thesis research found that a modification of the methodology currently used by NAVICP to predict repair prices can improve prediction accuracy, particularly for items with the highest replacement prices. Because repair prices are positively related to replacement prices, repairs of these items have the greatest fiscal impact. Improved prediction accuracy can be achieved by adopting a regression-based methodology, which in addition to improving prediction accuracy allows for the inclusion of multiple predictor variables. Although FSC was found to moderately improve the prediction accuracy, and LRC was found not to greatly improve the prediction accuracy of the regression models considered, only a limited number of potential predictors were examined. It is possible that a more extensive investigation would uncover predictors that substantially improve the prediction accuracy of these models.

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I. INTRODUCTION

A. INTRODUCTION

The research described in this thesis is the result of an initiative by Naval Inventory Control Point (NAVICP)-Philadelphia to replace its current methodology for predicting the repair prices of its inventory items. The focus of this research is the development of an improved methodology so as to provide a more accurate prediction of the costs of repairing Naval inventory items.

B. BACKROUND OF THIS RESEARCH

In 1999, the Navy adopted an initiative known as the Performance Based Logistics (PBL) that transfers traditional Department of Defense (DoD) inventory, supply chain and technical support functions to commercial contractors for a guaranteed level of performance at the same or, ideally, reduced cost [1]. Under the PBL program, the contractor is responsible for a range of activities including warehousing, transportation, repair/overhaul, technology insertion, engineering services, guaranteed reliability, and warranty management. An example of this concept was the award of a contract to The Boeing Company (hereafter known as Boeing) on May 2001 for a pilot program on F/A-18E/F Integrated Readiness Support Teaming, also known as the FIRST Program.

For the “FIRST” PBL initiative, NAVICP conducted a Business Case Analysis[1] (BCA) based on a five-year period to quantify any cost benefits that the Navy might realize due to this collaboration. These cost benefits can accrue from either cost avoidance or cost savings. The NAVICP BCA, using data from FY1995, indicated that an expected saving of $55.4 million (later adjusted to $52.4 million) was achievable over a five-year period. The analysis also anticipated savings of $73.7 million in cost avoidance relating to other integrated logistics support elements from the FIRST Program [1]. Thus the Navy anticipated a saving of $126.1 million contracting of FIRST program.

However, an audit conducted by the Department of Defense Office of the Inspector General (DoD IG) found that the business case that the Navy used to justify the award of the FIRST contract, overstated the cost of DoD performance by $268.9 million. Therefore, instead of the Navy’s claim of saving $126.1 million over the first five years, the analysis showed that the FIRST program actually cost the Navy $142.8 million more than the traditional support method [1]. Hence NAVICP was tasked to look into the accuracy of the business case analysis used extensively to develop these numbers. Chapter II provides a more detail description of the “FIRST” PBL as well as the BCA used in this program.

[1] BCA is a process designed to quantify cost area such as procurements, repairable, warehousing, maintenance cost etc used to determine Navy’s current cost.

C. OBJECTIVE AND SCOPE OF RESEARCH

The research described in the thesis was conducted under the sponsorship of the Operations Research group at NAVICP-Philadelphia. The aim of the research is to develop a predictive model for estimating the repair prices of components when the procurement price is known, but no actual repair data are yet available.

Inventory items are classified as either consumable or repairable, depending on whether they can be restored to ready-for-issue condition in a cost-effective manner when they fail. Accurate prediction of the cost of repairing an item is an important step in determining whether the item should be classified as consumable or repairable. It is also important to the effective management of the inventory system.

Repair prices for aviation and weapon system support can be difficult to predict. For example, an item could be repaired in one of several types of facilities, including Navy depots, inter-service depots or commercial facilities, thus resulting in large variations in repair prices. The ability to obtain accurate predictions and to quantify uncertainty in these predictions is important to defense organizations, which utilize them to determine the resources needed to fully optimize and fund its operations. Under-funding could result in a delay or cancellation of equipment replacement, whereas over-funding could deny resources to other operations.

In August 2003, the NAVICP Operations Research group was tasked to develop a methodology for improving prediction accuracy for repair prices, in light of the over-prediction of savings for the FIRST program. Because data on repair prices were not always available when conducting BCA for the FIRST program, NAVICP established the repair prices for newly provisioned items using the repair price matrix for estimating the repair prices versus historical data for similar items available at the Naval depots [1]. The repair matrix is based on a stratification of repairable items (mainly aviation and weapon system components) by replacement price into six different price categories. The ratio of the repair to replacement price is estimated within each category. Repair prices for newly provisioned items are determined by multiplying the replacement price with the appropriate ratio of repair to replacement prices. Chapter II discusses the repair matrix in detail, which was used as a baseline for comparison in the thesis research.

D. METHODOLOGY

To facilitate the thesis research, NAVICP provided data for 1,420 newly provisioned aviation and weapon system inventory items. Information of these inventory items include nomenclatures, federal stock class, local routing codes, replacement prices and repair prices. Other related repair processes and pricing information were subsequently obtained from the Material Budgeting and Industrial Support Departments at NAVICP.

This thesis reviews the appropriateness of various statistical analysis methodologies, in an attempt to improve the accuracy of repair-price predictions. The ratio-estimator model used by NAVICP does not allow for the use of other potential explanatory variables that may aid in predicting repair prices. Other methods, such as regression, can make use of a range of explanatory variables. This thesis describes statistical analyses to evaluate the benefits of including explanatory variables in addition to replacement price. The results of these analyses are then compared to predictive accuracy of the current methodology. All data analyses are performed using the statistical software package S-Plus®.

E. BACKGROUND OF NAVICP

The objective of this section is to provide a brief understanding of the operations of NAVICP. The mission of NAVICP is to provide program and support for the weapon systems that will keep its Naval forces mission-ready [7]. This mission is carried out by a single command organization operating as a tenant activity of Naval Support Activities in Mechanicsburg and Philadelphia.

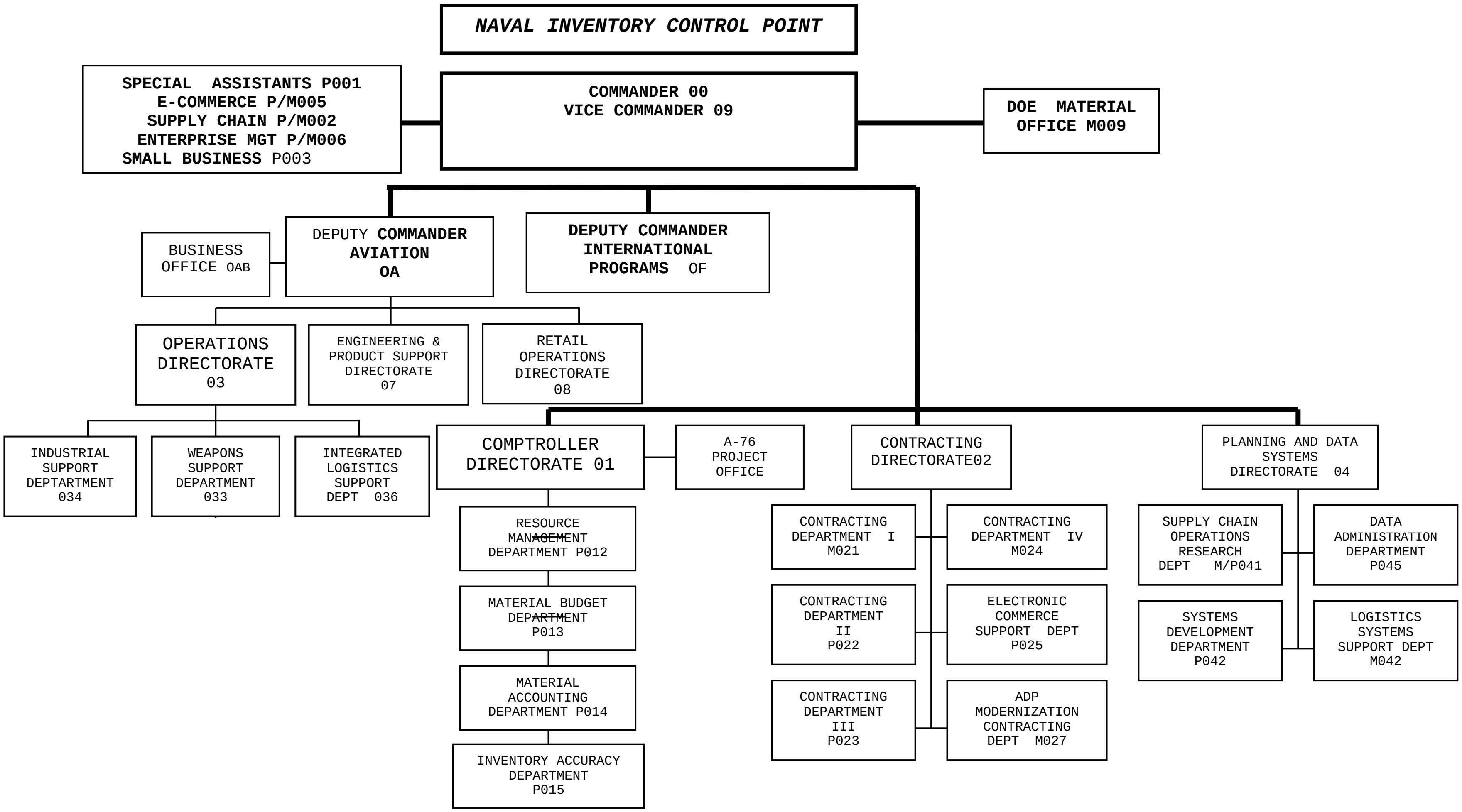
NAVICP was established in 1995, following the merging of Ships Parts Control Center (SPCC) in Mechanicsburg and Aviation Supply Office (ASO) in Philadelphia. This merger allowed the Navy to bring together all inventory support functions under a single command, ensuring a timely delivery of quality program and logistics support to keep

its Naval forces mission-ready [7]. The merger is also part of the Navy's effort to reduce cost and infrastructure activities as well as to standardize inventory management procedures.

The primary activity for the Philadelphia site is aviation and weapon system support. Among the aircraft supported are the F/A-18 and the V-22 as well as various engines, common avionics, and support equipment. In contrast, their Mechanicsburg counterpart handles support for hull, electrical, mechanical, and electronic components and repair parts for ships, submarines and weapon systems.

This section discusses the departmental activities of three main offices that are closely related to the accuracy of the repair price, namely Material Budgeting Department of Comptroller Directorate (P-code 013), Industrial Support Department of Operations Directorate (P-code 034) and Operations Research Department of Planning and Data Systems Directorate (P-code 0412). Figure 1 gives an overview of the NAVICP organization.

Figure 1. NAVICP Philadelphia Organization Chart [After, 10].

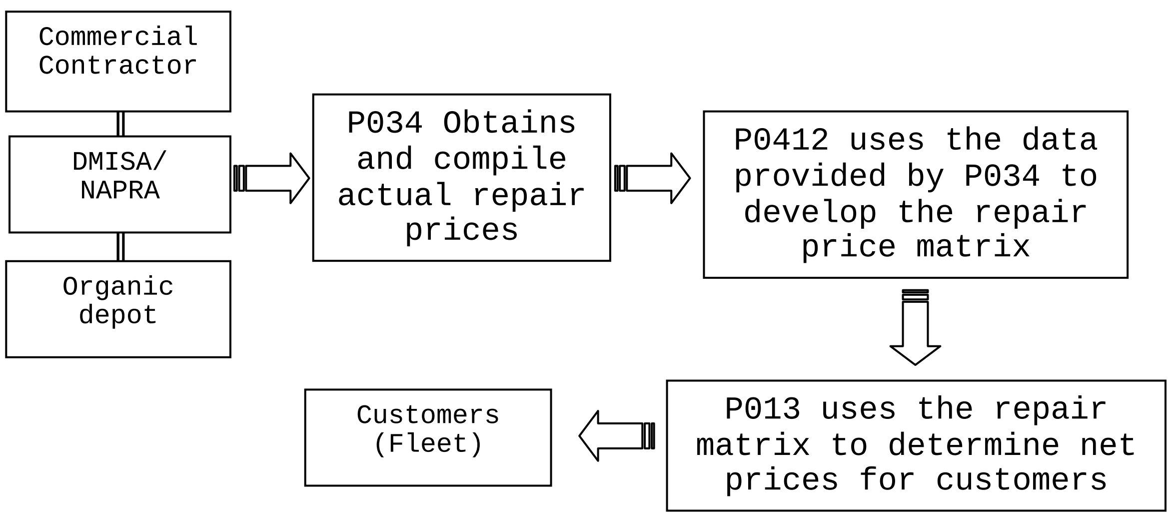


The Comptroller Directorate (P-code 01) is responsible for controlling the development, preparation and justification of all NAVICP budgetary requirements. Its Material Budget department administers and controls the financial aspects of inventory management, develops and justifies initial replenishment as well as repair budgetary requirements for Naval ship material support [4]. They are the primary users of the repair price matrix used to determine the final net price (including inflation, overheads, burdening, etc.) charges to the customer.

The primary functions of the Operations Directorate (P-code 03) involve providing supply policies, customer liaison, technical support and forecasting/planning of the Navy Aviation Operations. The Industrial Support Department is responsible for the execution and management of the Aviation Depot Level Repairable (AVDLR) repair program. The team coordinates component repair work executed by the Naval Aviation depots (NADEPs), and the Inter-Service component repair work executed by the Army Depots and Air Force Logistics Centers [8]. It obtains and compiles the repair pricing (from organic depot, DMISA/NAPRA and Commercial contractors) required for computation of budgetary and contracting requirements. Additionally, the team supports NAVAIR Scheduled Depot Level Maintenance (SDLM) functions and the Management Control Activity (MCA) for Government Furnished Material (GFM) contracts, and serves as the focal point for information and problem resolution associated with depot level repairs.

The Planning and Data Supply Directorate, P04, analyzes, develops and recommends plans, policies and procedures to improve practices and activities at NAVICP. The Operations Research group is responsible for developing the repair price matrix for estimation of repair prices. Figure 2 shows the activities of each department relating to repair prices.

Figure 2. Responsibilities of each department relating to repair prices.



F. THESIS ORGANIZATION

This thesis is divided into five chapters.

Chapter I gives an introduction to NAVICP and its organization responsibilities. It also describes the background for this thesis research, the objective and the methodologies used to conduct the research.

Chapter II discusses in detail NAVICP repair processes and its pricing methodologies and Business Case Analysis (BCA) used for Performance Based Logistics (PBL).

Chapter III describes the sources of data used, including filtering of unwanted information from the data. This chapter also looks into the current ratio methodology adopted by NAVICP as well as proposing an alternative ratio method that could help improve the prediction power of the repair matrix.

Chapter IV presents the results of the analysis and comparisons to the predictive accuracy obtained with the current pricing matrix.

Chapter V summarizes the research findings and presents recommendations for future research.

II. OVERVIEW OF NAVY REPAIR PROCESS

A. INTRODUCTION

This chapter describes in detail the U.S. Navy's repair processes (depot-level, commercial or inter-service) and its importance to budgeting and contracting. These processes were introduced in Chapter I in relation to the Performance Based Logistics effort for the "FIRST" program, which led to the investigation of the accuracy of its current methodology used in its Business Case Analysis for predicting repair prices.

B. OVERVIEW OF NAVICP REPAIR PROCESS

Repair price refers to the actual unit price that NAVICP pays to repair an item. The repair may be performed by any one or combination of the following;

1. Commercial facilities (definitized contract). Commercial repair information can be obtained from the Navy's contract status file. This file states the level of effort to inspect, repair and modify an item for that particular program.

2. Organic (Navy) depots (NADEPS). Repair performed at one of the three Naval repair facilities located in California, Florida and North Carolina. Repair pricing consists of actual material cost, labor cost and Navy Industrial Fund (NIF) rate[2].

[2] The NIF rate is established as a cost recovery rate for labor cost, overhead costs, transportation, etc. and may vary for different Designated Overhaul Points (DOP).

3. <u>Depot Maintenance Inter-Service Agreement (DMISA)</u>. Repairs performed through an inter-service agreement with the Army or the Air Force.

The projected repair price for each repairable item, which is stored in data element B055A, is usually updated annually and does not actually display the "latest" price. NAVSUP directives concerning repair price updates for repairable items dictate that it recover any losses over a period of approximately twelve-fifteen months. For a given item, the repair price in B055A represents a computed weighted average repair price for any or all members of the family, and from all sources. Thus, each inventory item classified as either a head or member of the family, depending on the importance of the components in its family, will have the same computed weighted average repair price.

Repair prices are determined by computing weighted averages of prices, with the weights proportional to the number of items repaired at each price category. For example, there may be commercial orders and organic repairs, for a particular item, from two Navy depots (NADEP) that contribute to an average price of $14,190 as shown in Table 1. Thus, the fleet could pay $14,190 even though the repair price may cost $22,500.

Table 1. Computed Weighted Average Pricing Methodology

NIIN	Nomenclature	Source	Qty	Price	Total
011199660	Amplifier	Organic 1	2	$22,500	$45,000
	Radio	Organic 2	6	$9,800	$58,800
		Commercial	12	$15,000	$180,000
		Total	**20**		**$283,800**
		Average			**$14,190**
	New Repair Price		**$14,190**		

NIIN is the identification number of the inventory item. Source refers to where the repair was performed.

Every year, the Industrial Support Department provides the list of organic as well as DMISA repair prices. These updated repair prices are then used by the NAVICP Operations Research group to generate the repair-price matrix to predict repair prices for newly provisioned items. The material budgeting department then uses these prices to determine the standard and net prices[3], which include cost recovery for transportation, depot washout, obsolescence, testing, taxes etc., as illustrated above in Figure 2.

[3] Standard Price is the price the customer pays for a new issue for a consumable or Aviation Depot Level Repairable (AVDLR) item. Net Price is the price the customer pays for an AVDLR with carcass turn-in. These prices are determined by multiplying a cost recovery rate to the repair prices.

C. PERFORMANCE BASED LOGISTICS FOR F/A-18E/F AIRCRAFT

Under the PBL program, NAVICP awards a contract to a single supplier. This supplier then provides the material directly to the fleet in time to meet the customer’s requirement. This is achieved without the intervention of, or need for, government inventory managers or intervening storage and material handling systems while providing increased product reliability and reducing total cost to the Fleet Customer and the Navy [6]. One of first contracts issued under the PBL program on May 2001 was for the F/A-18E/F Integrated Readiness Support Team program. NAVICP awarded Boeing a five-year contract with an award-fee provision based on performance requirements. The contract covered procurement of initial and replenishment spares for 519 repairable parts and 5856 consumable parts as well as repair of the repairable parts [1].

For each PBL initiative, NAVICP and NAVAIR conduct a Business Case Analysis (BCA) to justify the amount of cost savings or cost avoidance[4] benefits through the contract. The BCA process involves determining the Navy’s current cost of doing business. For the FIRST Program, the “without FIRST” cost is compared with the cost to the Navy under a PBL arrangement. The “with FIRST” cost includes both the PBL supplier’s costs as well as residual costs that the Navy will retain even under a PBL arrangement. Some cost areas considered in the BCA are depot repair, wholesale and retail spare parts procurements, warehousing,

[4] Cost avoidance is calculated based on overheads, operations and labor saving by NAVICP due to logistic support.

transportation, fleet maintenance labor, fleet consumables, sustaining engineering, NAVICP operating costs, PBL administrative costs and other miscellaneous costs [5].

A BCA conducted by NAVICP indicated that an expected savings of $55.4 million (later adjusted to $52.4 million) was likely over a 5-year period from the FIRST program. The analysis also found that savings of $73.7 million in cost avoidance relating to other integrated logistics support elements from the FIRST program was achievable. Table 2 summarizes the Navy's reported five-year $126.1 million cost avoidance relating to the FIRST contract with Boeing [1].

Table 2. FIRST Program Savings (1999) - Without FIRST and With FIRST (in millions of dollars) [1].

Description	Without FIRST	With FIRST	Cost Increase/ (Cost Avoidance)
NAVICP BCA			
Material costs	$779.00	$771.50	$(7.50)
Operations cost	$108.10	$63.20	$(44.90)
Subtotal NWCF cost	$887.10	$834.70	$(52.40)
NAVAIR BCA			
Non-supply support elements	$1,531.20	$1,457.50	$(73.70)
Total	**$2,418.30**	**$2,292.20**	**$126.10**

Non-supply support elements refer to cost avoidance due to engineering, integrated logistic support, information systems and supporting equipment. Cost avoidance is calculated based on overheads, operations and labor saving by NAVICP due to logistic support.

However, DoD IG found that these claimed savings were overstated, and that the FIRST program actually resulted in a cost increase of $142.8 million. Table 3 summarizes the adjustments made to the BCA [1]. The huge difference in the estimation of cost savings led to an investigation. It appears that NAVICP used an outdated repair price matrix to perform the business case analysis for determining repair price of an item with little or no historical cost data (i.e. newly provisioned items) [1].

Table 3. DoD IG Corrected FIRST Program Savings [1].

Description	IG Corrected Without FIRST	IG Corrected With FIRST	Cost Increase/ (Cost Avoidance)
NAVICP BCA			
Material costs	$ 573.80	$ 783.10	$ 209.30
Operations cost	$ 119.50	$ 63.20	$ (56.30)
Subtotal NWCF cost	$ 693.30	$ 846.30	$ 153.00
NAVAIR BCA			
Non-supply support elements	$ 1,531.20	$ 1,521.00	$ (10.20)
Total	**$ 2,224.50**	**$ 2,367.20**	**$ 142.80**

Non-supply support elements refer to cost avoidance due to engineering, integrated logistic support, information systems and supporting equipment. Cost avoidance is calculated based on overheads, operations and labor saving by NAVICP due to logistic support.

D. THE NAVICP METHODOLOGY FOR PREDICTION OF REPAIR PRICES

This section describes how NAVICP uses actual repair prices to generate the repair price matrix, and the importance of these costs to the accuracy of this matrix.

NAVICP developed the repair price matrix in 1986, based on a study of actual repair prices of items across all weapon systems and aviation items that had procurements in the previous two years. The repair matrix groups inventory items based on replacement price into six categories. Within each category, repair price is predicted by applying a common multiplier to the replacement price. The multiplier is calculated by taking the average of the ratios of repair to replacement price. For a newly provisioned item (that has not generated a repair history), its repair price is predicted by multiplying its replacement price by the appropriate multiplier. For example, the multiplier for items with replacement prices less than $999 (Category 1) is 48%, and an item with a replacement price of $800 has a predicted repair price of $384.00 (48% of $800). This repair price matrix used by NAVICP in justifying cost saving from the FIRST program is shown in Table 4.

Table 4. Repair Price Matrix used for FIRST Program in 1995 [After, 1].

Replacement Price of Inventory Item (dollars)	Predicted Repair Price, as Percentage of Replacement Price
1 – 999	48
1,000 - 2,999	32
3,000 - 9,999	30
10,000 - 24,999	24
25,000 - 49,999	20
50,000 +	15

The percentage in the second column is the average of the ratios of repair to replacement price across all items in the corresponding category.

III. OVERVIEW OF CURRENT METHODOLOGY

A. INTRODUCTION

This chapter describes the source of data used in the analysis. It also describes the current prediction methodology adopted by NAVICP, and it proposes an alternative method that could help improve prediction accuracy.

B. DATA USED IN THIS RESEARCH

The data used for the cost estimation are obtained from the Master Data File from NAVICP’s Oracle server. This data file is widely used in NAVICP for tracking inventories, quarterly demands, replacement and repair prices etc. The data also include other variables that may be useful in predicting repair prices. An excerpt of the data used for the analysis in this thesis is shown in Table 5.

Table 5. An Excerpt of the Data Used in the Thesis Research.

COG	FSC	NIIN	NOMENCLATURE	REPL_ PRICE	RPR_ PRC	FRC	FGC	LRC
7R	5930	000083636	SWITCH ASSEMBLY	4242	1081	H	W6AB	QAC
7R	5985	000014545	SWITCH	10412	1296	H		DMF
7R	6110	000016632	REGULR,VOLTAGE	19021	648	H		DTQ
7R	1620	000049840	PISTON ASSEMBLY	31093	9179	H		MXD
1R	2840	998149318	RING, COMPRESSOR	6805	0	H		SVA
7R	1560	008666688	TANK,FUEL, AIRCRAFT	20210	3998	H		LHF
0R	6130	014663481	POWER SUPPLY	695	144	H		T16
7R	5998	012019353	CIR.CARD ASSY	5352	739	H		Q3C

COG is the Cognizance Codes which is used to identify if item is repairable or consumable. FSC is the Federal Stock Class assigned to each item to classify them into different categories. NIIN is the National Item Identification number used to identify an approved inventory item. FRC is the Family Relationship Code which identifies if an item is the head or member of the family. FGC is the Family Group Code used to identify an item within a family. LRC is the Local Routing Code used to determine the internal organizational component (by Platform) to which item inputs are to be routed for action.

The first three fields (COG, FSC and NIIN) give the identity of the supply item. COG is the Cognizance Code, which is used to identify an item as repairable or consumable. Items with COG code ‘0R’ are funded and managed through special appropriations. Code ‘1R’ refers to items that are non-repairable, also known as consumables. Code ‘7R’ refers to items that are repairable.

Federal Stock Class (FSC) is a four digit code assigned to each item to classify them into different categories, such as aircraft fuel pumps, compressors or circuit boards. Appendix A shows a full listing of FSC codes used in this analysis. The national item

identification number (NIIN) is an eight-digit code used to uniquely identify an inventory item. The family relationship code (FRC) identifies an item as either the head or member of its family. Each family of items is identified by a family group code (FGC) that is blank if the family consists of a single item (also known as a bachelor item). The local routing code (LRC) is a three-letter code used to determine the internal organizational component to which item inputs are to be routed for action. The first letter of the code identifies the platform group that manages the items. Appendix A shows a full listing of LRC codes used in this analysis.

The data set includes a total of 1,420 newly provisioned inventory items available from January to June 2003. Not all the information in the data set provided by NAVICP is appropriate for this analysis. Table 6 shows a list of items to be excluded from the analysis.

Table 6. Filtering of data set to be used for this analysis

Total number of Inventory Items	1420
Less	
1. Items with COG = ‘0R’ or ‘1R’	21
2. Items with lack of data or Repair Price ≤ 0	6
3. Items that are not head of the family	50
Total number of Items deemed useful for this analysis	1343

Items with COG code ‘0R’ are funded and managed through special appropriations whilst items with Code ‘1R’ are categorized as non-repairable, also known as consumables. Hence, predicting the repair prices for these twenty one items would not be of fair representation or accurate. Only items with Code 7R, items that are repairable, are considered in this analysis.

There are four inventory items that have no information other than the inventory identification number. Also, there are two items with no repair price information and, therefore, these data are removed from the data set.

NAVICP groups repair price data by families of items. Each item within a family has the same estimated repair price. To avoid using redundant information, only the data reported for the head of the family are used. Fifty items corresponding to non-head members of families are removed from the analysis.

C. CURRENT PREDICTION METHODOLOGY

The current methodology adopted by NAVICP is to determine the average of the ratios of repair to replacement price across all inventory items within a specified category. There are a total of six different categories based on replacement price. The following shows the calculation used to determine the average cost ratio for category j:

$$\hat{\beta}_j = \sum_{i=1}^{n_j} W_{ij} \frac{Y_{ij}}{X_{ij}},$$

where Y_{ij} and X_{ij} are the repair and replacement prices, respectively, for item i in category j. In this notation a weight denoted W_{ij} is also used to calculate the average. NAVICP uses equal weights, $W_{ij} = 1/n_j$, to calculate the average ratio, where n_j is the number of items in category j. The predicted repair price for an item having no historical repair price data, with replacement price X belonging to category j, is then given by $\hat{Y} = \hat{\beta}_j X$.

Based on the data provided by NAVICP (total of 1,420 inventory items), the current repair matrix is shown in Table 7. This table also presents a summary of the variability and correlation between repair and replacement prices for these items. From Table 7, it is observed that there is moderate correlation between replacement and repair prices for majority of the price categories, which indicates that a strong linear relationship between the two variables is unlikely to exist. This implies that using replacement price as the sole variable to predict the

repair price will leave unexplained much of the variability in repair prices.

Table 7. Current Repair Price Matrix

Price Category	Number of Items	Correlation between repair and replacement price	Predicted Repair Cost, as Percentage of Replacement Price
UP TO $999	33	0.561	60.91
$1,000 TO $2,999	188	0.269	42.52
$3,000 TO $9,999	457	0.238	34.01
$10,000 TO $24,999	354	0.282	25.14
$25,000 TO $49,999	155	0.281	18.44
$50,000 AND ABOVE	156	0.283	16.00
Overall	1343	0.447	-

The percentage in the last column is the average of the ratios of repair to replacement price across all items in the corresponding category.

D. MODIFIED RATIO METHODOLOGY

An alternative ratio method is considered where the weights W_{ij} are chosen to be proportional to X_{ij}. These ratio estimators take the following form:

$$\hat{\beta}_j = \frac{\overline{Y}_j}{\overline{X}_j},$$

where $\overline{Y}_j$ and $\overline{X}_j$ are the average repair and replacement prices, respectively, for all items in category j. Items with higher replacement prices in a category are assigned more weight using the modified ratio method than with the method currently used by NAVICP. Results of applying the modified ratio method to the 1,343 items used in the analysis are shown in Table 8.

Table 8. Repair Price Matrix (Modified Ratio Method)

Price Category	Number of Items	Predicted Repair Price, as Percentage of Replacement Price
UP TO $999	33	59.36
$1,000 TO $2,999	188	41.68
$3,000 TO $9,999	457	32.56
$10,000 TO $24,999	354	24.90
$25,000 TO $49,999	155	18.64
$50,000 AND ABOVE	156	12.40
Overall	1343	-

The percentage in the last column is the average of the ratios of repair to replacement price across all items in the corresponding category.

E. A COMPARISON OF RATIO PREDICTION METHODOLOGIES

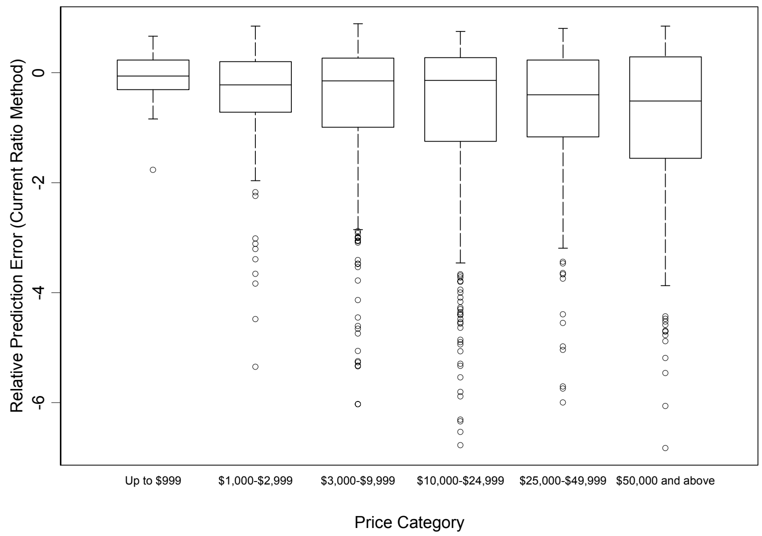
A box plot provides an excellent way to visualize many aspects of a distribution in a data set, particularly determining the median and variation changes between different categories. Figure 3 and Figure 4 show the median, variability and outliers of the relative prediction error (between repair and predicted repair prices) using the current and modified ratio methodology respectively. Relative prediction error is defined as follows:

$$R_i = \frac{\left(Y_i - \hat{Y}_i\right)}{Y_i}.$$

It should be noted that data points with relative prediction error greater than 0.7 are eliminated to enhance graphical display.

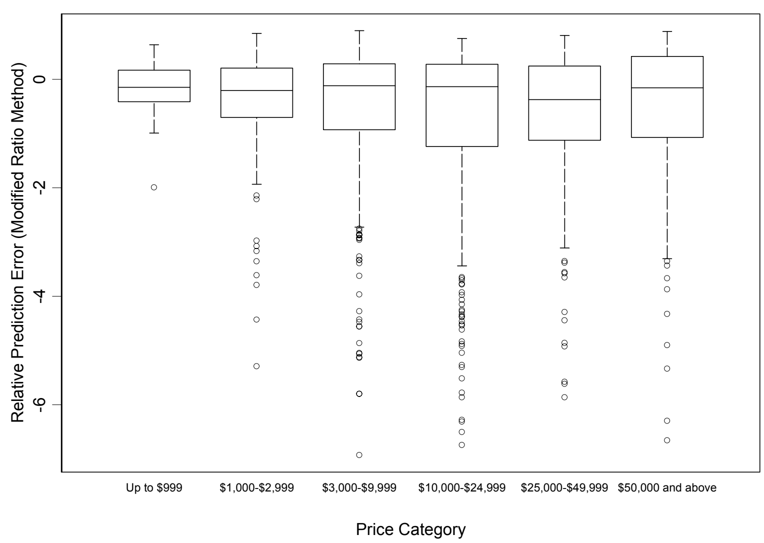
It is observed that the spread increases with each price categories and large error can be seen in the region of the higher priced categories for both plots. For both methodologies, the median and variations are reasonably similar for price categories below $50,000. Slight improvement in the prediction error can be seen in the last categories for inventory items with replacement prices of $50,000 and above.

Figure 3. Box Plots of Relative Prediction Errors, By Category, for the Current Ratio Method



A total of 37 out of 1343 data values, with relative prediction error greater than 0.7, were excluded to better enhance graphical display.

Figure 4. Box plots of Relative Prediction Errors, By Category, for the Modified Ratio Method



A total of 33 out of 1343 data values, with relative prediction error greater than 0.7, were excluded to better enhance graphical display.

In Table 9, it is rather evident that both methods show little success when predicting repair prices for inventory items with replacement prices greater than $10,000. Again, the largest error can be seen in the last category, whereby 75 percent of the observations have approximately 245 percent prediction errors for the current ratio method. The modified ratio method shows an improvement, but still, the relative prediction errors are greater than or equal to 160 percent for almost 25 percent of items in this category.

Both ratio methods indicate that replacement price alone may be a poor predictor of the repair price, and that the relationship between the two analyzed variables may be non-linear. Chapter IV investigates the use of a logarithmic transformation in the regression method, as well as including categorical variables, that may help to improve the prediction of repair prices.

Table 9. Quantiles of Absolute Relative Prediction Error (Percentages) of current and modified ratio method.

Category	Sample Size	Current Ratio Method				Modified Ratio Method			
		25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile	Mean
up to $999	33	16.47	28.96	38.66	32.59	16.48	25.95	46.35	36.31
$1,000 - $2,999	188	21.37	36.94	75.59	71.28	20.91	37.07	73.92	70.39
$3,000 - $9,999	457	22.70	47.12	106.44	96.90	22.08	45.62	99.72	93.29
$10,000 - $24,999	354	23.33	52.63	140.33	131.67	23.42	52.52	139.34	131.04
$25,999 - $49,999	155	30.74	61.38	146.42	170.38	30.22	62.14	141.60	166.56
$50,000 and above	156	40.26	78.18	245.32	320.73	37.21	65.14	160.36	234.88

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IV. METHODOLOGY

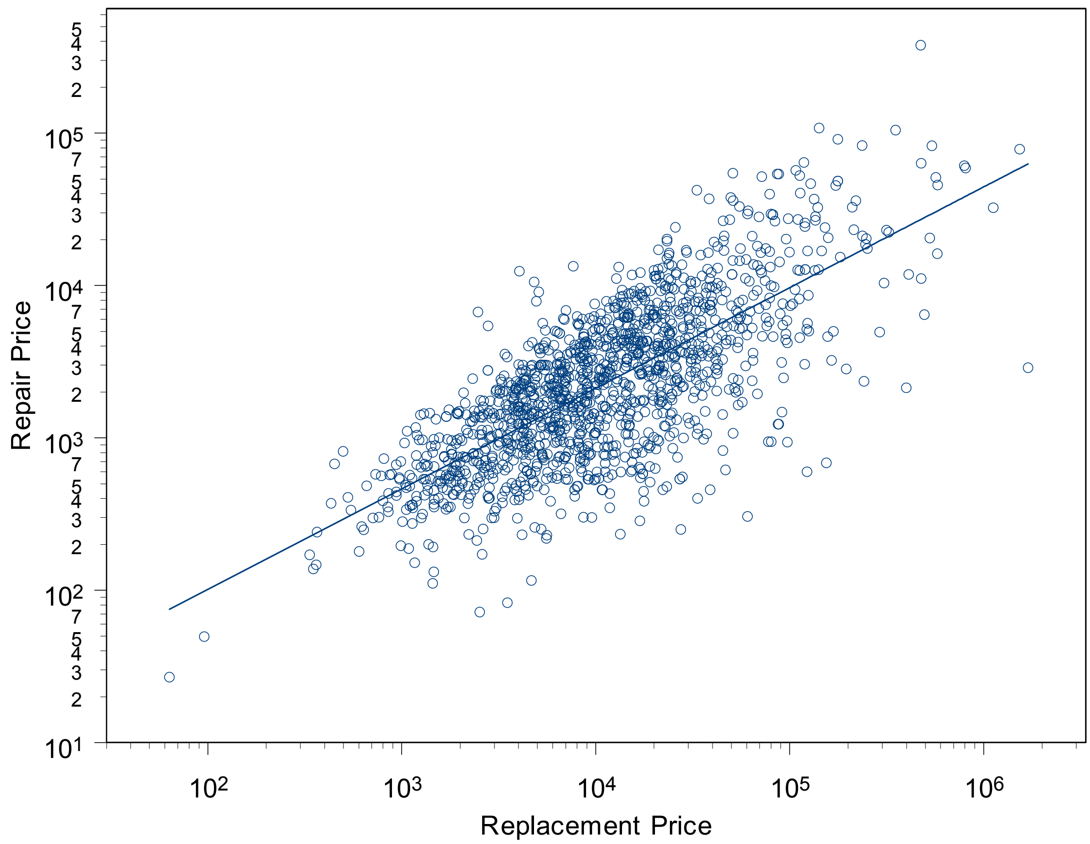
A. INTRODUCTION

In this chapter attention is focused on the use of regression models to predict the repair price of an inventory item from its replacement price and possibly other explanatory variables. This chapter will look at regression analysis with logarithmic terms as well as categorical variables such as Federal Stock Class, Family Relationship Code and Local Routing Code that may help to improve prediction accuracy.

B. REGRESSION ANALYSIS

Regression analysis is used to develop a mathematical model that describes the relationship of repair prices of inventory items to other variables. Regression models considered in the thesis research are linear, possibly after taking nonlinear transformations of the response and/or explanatory variables. Scatter plots are examined in order to better understand the relationship between variables. Figure 5 shows the scatter plot of repair prices versus replacement prices on a logarithmic scale. The relationship between the two variables can be reasonably described as linear on a logarithmic scale. The decision was therefore made to examine regression models with logarithm transformations applied to these two variables.

Figure 5. Scatter plot of repair prices versus replacement prices for 1,343 repair items in the Naval inventory.



The simple logarithmic transformed regression model (Model I) is expressed as follows:

$$\log\left(\frac{Y_i}{X_i}\right) = \beta_0 + \beta_1 \log(X_i) + \varepsilon_i \,,$$

where X_i and Y_i are the replacement and repair prices, respectively, for inventory item i. The intercept and slope coefficients are β_0 and β_1, and ε_i is the error term. It is assumed that the error terms ε_i are independent, normally distributed random variables with mean zero and a common (but unknown) variance σ^2. Least-squares regression was

used to estimate the coefficients of the regression model, using the statistical software package S-Plus® on data consisting of replacement and repair prices for 1,343 Naval inventory items. The least squares estimates are shown in the following table:

Table 10. Least-squares Regression Coefficient for the Simple Regression Model, Based on *n* = 1,343 Items.

Coefficient	Estimate	Standard Error	t-ratio
Intercept ($\hat{\beta}_0$)	1.5858	0.1571	10.0687
Slope ($\hat{\beta}_1$)	-0.3403	0.0168	-20.2806

Values of the t-ratio that exceed 1.96 in absolute value are statistically significant at the α = .05 test level.

From Table 10, it is seen that the logarithm of replacement price is a statistically significant predictor of the logarithm of the ratio of repair price to replacement price. To predict the repair price the following nonlinear transformation is used:

$$\hat{Y}_i = X_i \exp(\hat{\beta}_0 + \hat{\beta}_1 \log X_i) .$$

C. REGRESSION ANALYSIS WITH CATEGORICAL VARIABLES

One of the advantages of regression models compared to ratio-estimator models is the ability of the former to incorporate predictor variables of diverse types. NAVICP collects data on a wide range of attributes for the repairable items that it manages, much of which is categorical. In the data set provided by NAVICP, as shown

in Table 5, are attributes such as Federal Stock Class (FSC) and Local Routing Code (LRC) that groups these inventory items into their respective functions and/or platform types. In this section regression models that incorporate these categorical attributes as predictors is examined.

In the data provided by NAVICP, restricted to 1,343 inventory items that were used in analyses, a total of 101 different FSC levels and 18 different LRC levels were represented. For model-building purposes only those levels with twenty or more inventory items were considered as potential predictor variables. These levels are shown below in Table 11.

Table 11. FSC and LRC levels with twenty or more inventory items.

FSC	Description	Number of inventory items	LRC	Description	Number of inventory items
5998	Circuit Card Assemblies	240	A$$	F/A18 A/D	205
1560	Airframe Structural Components	126	C$$	AV-8B	69
2840	Aircraft Engines and Turbines Components	102	D$$	EA-6B	64
1615	Helo Rotor Blades Mechanisms	74	E$$	F-14	77
1650	Aircraft Hydraulic Components	72	H$$	S-3	48
1620	Aircraft Landing Gear Components	60	L$$	P-3	74
1680	Miscellaneous Aircraft Components	58	M$$	E-2	69
5895	Miscellaneous Communication Equipment	41	Q$$	Common Systems	78
6625	Electronic Testing Instruments	39	S$$	Aircraft Engines	130
6130	Non-rotating Electrical Converters	35	T$$	Aviation Support Systems	83
5985	Antennas Related Equipment	26	U$$	Aviation Support Systems	101
4920	Aircraft Maintenance Equipment	22	V$$	H-1/H-46	98
6150	Miscellaneous Electrical Power Equipment	22	X$$	H-3/H-56	122
2915	Aircraft Fuel Systems Components	21	Y$$	H-60	97
5841	Airborne Radar Equipment	20			

LRC is represented by the first character of the code. For example, A$$ refers to all LRC codes that begin with the letter "A".

F-tests for significance of regression were performed to determine if FSC and LRC contributed significantly to the prediction of $\log(Y_i/X_i)$. Models II and III include FSC and LRC, respectively, as categorical variables while Model IV includes a combination of both FSC and LRC variables. These models were fit two different ways:

Intercept-only models. These models incorporate FSC and/or LRC as indicator variables, and the logarithm of replacement price as a numeric predictor. Intercept-only models regression allow for the possibility that only the intercepts of the regressions vary with the categorical predictors.

Intercept-and-slope models. These models incorporate the same predictor variables as the intercept-only models, and the products of the indicator variables with the logarithm of replacement price as predictors. Intercept-and-slope models allow both the intercepts and slopes of the regressions to vary with the categorical predictors.

Table 12 tabulates the result of the F-test for intercept for Models II, III, and IV fit as intercept-only models. For all three models, the null hypothesis is rejected, thus it can be concluded that using different intercept terms for FGC and LRC categories helps to predict repair prices.

Similarly the models with slope terms are tested under the null hypothesis that the slope terms do not help to improve prediction power over their intercept-only counterparts. As shown in Table 13, the inclusion of slope terms leads to a statistically significant improvement in prediction power for Models III and IV, but not for Model II.

The next step is to perform stepwise regression to select a subset of variables that are significant as predictors. A commonly used form of stepwise regression is forward inclusion. Using statistical software package S-Plus®, the default method of Efroymson's forward selection procedure is employed. This selection procedure starts with an empty subset and at each step adds the independent variable that gives the largest reduction of the residual sum of squares. As each variable is added to this subset, partial correlations are considered to see if any of the variables in the subset should be dropped [11]. Table 14, 15 and 16 summarize the regression models by reporting their coefficients, standard errors and t-ratios.

Table 12. F-test for Categorical Predictor Models, Intercepts Only

Model	**II (FGC)**	**III (LRC)**	**IV (FGC and LRC)**
Unexplained variation for the full model, SSE_0	818.980	852.124	795.284
Degrees of Freedom, P_0	17	16	31
Unexplained variation for Model I, SSE_1	892.553	892.553	892.553
Degrees of Freedom, P_1	2	2	2
Test statistic value, F-test $= \left(\dfrac{\frac{SSE_1 - SSE_0}{p_0 - p_1}}{\frac{SSE_0}{n - p_0}} \right)$	7.941	4.497	5.533
Test statistic critical value with significance level of 0.05, $F_{.05, p_0 - p_1, n - p_0}$, n = 1,343	1.639	1.699	1.476
Conclusion (α = .05)	H_0 Rejected	H_0 Rejected	H_0 Rejected

The null hypothesis is that the additional predictors in Models II, III, or IV do not improve the prediction power of Model I.

Table 13. F-test for Categorical Predictor Models, Intercepts and Slopes

Model	**II (FGC)**	**III (LRC)**	**IV (FGC and LRC)**
Unexplained variation for the full model, SSE_0	805.843	825.412	766.041
Degrees of Freedom, P_0	32	30	60
Unexplained variation for the intercept-only models, SSE_1	818.980	852.124	795.284
Degrees of Freedom, P_1	17	16	31
Test statistic value, F-test $= \left(\dfrac{\frac{SSE_1 - SSE_0}{p_0 - p_1}}{\frac{SSE_0}{n - p_0}} \right)$	1.425	3.035	1.689
Test statistic critical value with significance level of 0.05, $F_{.05, p_0 - p_1, n - p_0}$, n = 1,343	1.674	1.699	1.476
Conclusion	H_0 Accepted	H_0 Rejected	H_0 Rejected

The null hypothesis is that the slope terms in Models II, III, or IV do not improve the prediction power over the intercept-only counterparts.

Table 14. Stepwise Regression of Best Possible Selection for Predictor using only intercept terms for Model II (FSC grouping).

Coefficient	Estimate	Standard Error	t-ratio
Intercept	1.8154	0.1567	11.5842
$Log(X_i)$	-0.3700	0.0166	-22.2745
FSC Code 5998	-0.2741	0.0591	-4.6355
FSC Code 1560	0.3323	0.0762	4.3616
FSC Code 1615	0.5104	0.0960	5.3178
FSC Code 1620	0.3800	0.1055	3.6022
FSC Code 1680	0.3039	0.1071	2.8378
FSC Code 6625	0.3128	0.1291	2.4224
FSC Code 5841	-0.5524	0.1783	-3.0978
R^2	0.2954		

Values of the t-ratio that exceed 1.96 in absolute value are statistically significant at the α = .05 test level and are used as criteria for adding variables to the subset when using Efroymson's method.

Table 15. Stepwise Regression of Best Possible Selection for Predictor Using both intercept and slope terms for Model III (LRC grouping).

Coefficient	Estimate	Standard Error	t-ratio
Intercept	1.6890	0.1685	10.0215
$Log(X_i)$	0.1981	0.0656	3.0226
LRC Code E	-0.2754	0.0956	-2.8822
LRC Code U	0.2025	0.0836	2.4215
LRC Code X	-1.0895	0.5503	-1.9800
LRC Code Y	-1.3794	0.6097	-2.2622
LRC Code A x $Log(X_i)$	-0.3574	0.0180	-19.8133
LRC Code Y x $Log(X_i)$	0.1411	0.0589	2.3956
R^2	0.2699		

Values of the t-ratio that exceed 1.96 in absolute value are statistically significant at the α = .05 test level and are used as criteria for adding variables to the subset when using Efroymson's method.

Table 16. Stepwise Regression of Best Possible Selection for Predictor using both intercept and slope terms for Model IV (Includes both FSC and LRC groupings).

Coefficient	Estimate	Standard Error	t-ratio
Intercept	**1.6598**	**0.1567**	**10.5913**
Log(X_i)	**0.0371**	**0.0092**	**4.0498**
FSC Code 1560	**0.3307**	**0.0759**	**4.3556**
LRC Code E	**-0.2728**	**0.0928**	**-2.9407**
LRC Code U	**0.2572**	**0.0820**	**3.1343**
FSC Code 5998 x Log(X_i)	**-0.3562**	**0.0167**	**-21.3800**
FSC Code 1560 x Log(X_i)	**-0.0317**	**0.0065**	**-4.8461**
FSC Code 1650 x Log(X_i)	**0.0430**	**0.0101**	**4.2616**
FSC Code 1680 x Log(X_i)	**0.0461**	**0.0110**	**4.2134**
FSC Code 5895 x Log(X_i)	**0.0335**	**0.0115**	**2.9208**
LRC Code A x Log(X_i)	**-0.0528**	**0.0174**	**-3.0336**
LRC Code U x Log(X_i)	**0.0214**	**0.0108**	**1.9815**
R^2	**0.3146**		

Values of the t-ratio that exceed 1.96 in absolute value are statistically significant at the α = .05 test level and are used as criteria for adding variables to the subset when using Efroymson's method.

To predict the repair price the following transformation is used:

- For Model II(FSC Code with intercept terms only):

$$\hat{Y}_i = X_i \ \exp\left(\hat{\beta}_0 + \hat{\beta}_1 \log X_i + \hat{\beta}_2 F_{5998,i} + \hat{\beta}_3 F_{1560,i} + \hat{\beta}_4 F_{1615,i} + \hat{\beta}_5 F_{1620,i} + \hat{\beta}_6 F_{1680,i} + \hat{\beta}_7 F_{6625,i} + \hat{\beta}_8 F_{5841,i}\right)$$

where, for example,

$$F_{5998,i} = \begin{cases} 1, & \text{item } i \text{ has FSC code 5998} \\ 0, & \text{otherwise} \end{cases}$$

and other FSC codes are represented similarly.

- For Model III (LRC Code with both intercept and slope terms):

$$\hat{Y}_i = X_i \ \exp\left(\hat{\beta}_0 + \hat{\beta}_1 \log X_i + \hat{\beta}_2 L_{E,i} + \hat{\beta}_3 L_{U,i} + \hat{\beta}_4 L_{X,i} + \hat{\beta}_5 L_{Y,i} + \beta_6 L_{A,i} \log X_i + \hat{\beta}_7 L_{Y,i} \log X_i\right)$$

where, for example,

$$L_{A,i} = \begin{cases} 1, & \text{item } i \text{ has LRC code beginning with "A"} \\ 0, & \text{otherwise} \end{cases}$$

and other LRC codes are represented similarly.

- Model IV(FSC and LRC Code with both intercept and slope terms)

$$\hat{Y}_i = X_i \exp\Big(\hat{\beta}_0 + \hat{\beta}_1 \log X_i + \hat{\beta}_2 F_{1560,i} + \hat{\beta}_3 L_{E,i} + \hat{\beta}_4 L_{U,i} + \hat{\beta}_5 F_{5998,i} \log X_i + \hat{\beta}_6 F_{1560,i} \log X_i$$
$$+ \hat{\beta}_7 F_{1650,i} \log X_i + \hat{\beta}_8 F_{1680,i} \log X_i + \hat{\beta}_9 F_{5895,i} \log X_i + \hat{\beta}_{10} L_{A,i} \log X_i + \hat{\beta}_{11} L_{U,i} \log X_i\Big)$$

D. RESULTS OF ANALYSIS

Figure 6 shows box plots of the relative prediction errors for each of the four regression models that were considered. Again, Model I use only $\log(X)$ (the logarithm of replacement price) as a predictor variable for $\log(Y/X)$ (the logarithm of the ratio of repair price to replacement price). Model II includes FSC categories into the model, Model III includes LRC categories into the model, and Model IV includes both FSC and LRC categories into the model. Relative prediction error is given by the following:

$$\hat{R}_i = \frac{Y_i - \hat{Y}_i}{Y_i},$$

where

$$\hat{Y}_i = X_i \exp(\hat{L}_i),$$

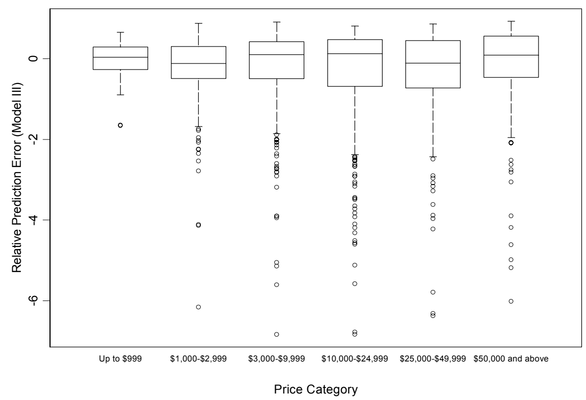
and $\hat{L}_i$ is the fitted value of $\log(Y_i / X_i)$.

The box plots indicate that the spread in relative prediction errors increases moderately with the replacement price; i.e., more expensive items have larger prediction errors not only in an absolute sense, but also as a percentage of the replacement price. However, relative errors in the highest price category are reduced when compared to the modified ratio method as described in Chapter III. Model I, II and IV displayed rather similar results in terms of relative prediction error in the highest price category. Regression with the inclusion of categorical variables shows slight improvement in relative prediction error.

Table 17 also indicates that for 75 percent of the observations, the relative prediction error ranges from 89 percent to 96 percent.

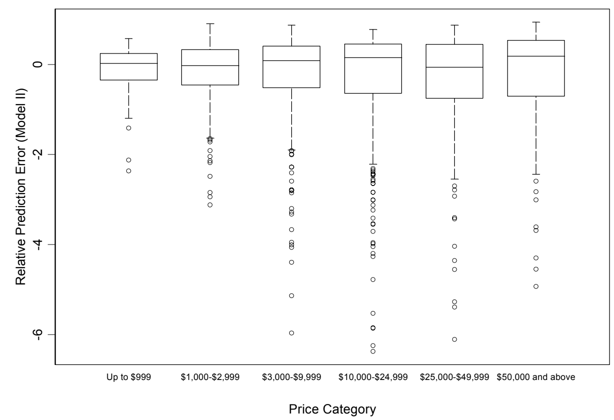
Figure 6. Box Plots of Relative Prediction Errors for Each Price Category for All Models

Model I



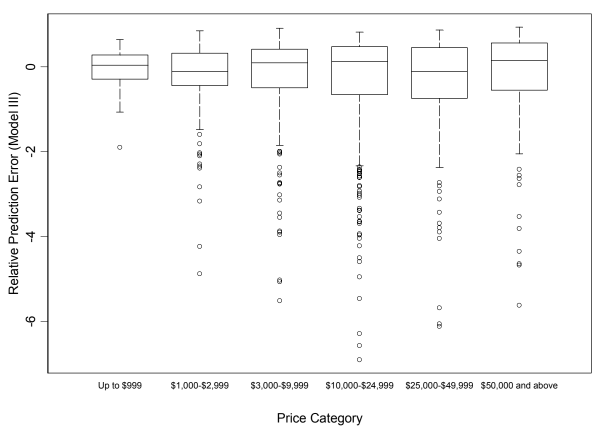
A total of 18 data values were excluded to better enhance graphical display.

Model II



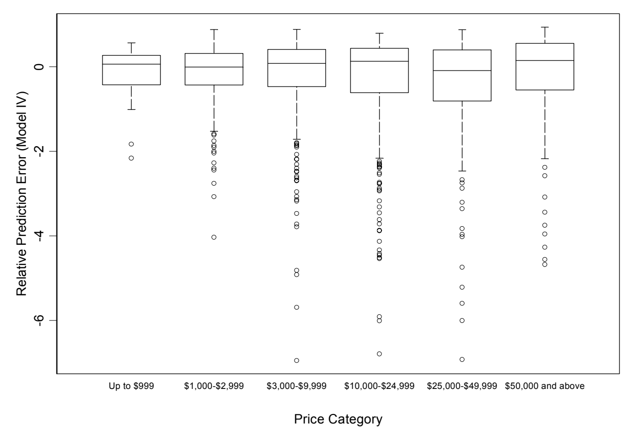
A total of 18 data values were excluded to better enhance graphical display.

Model III



A total of 17 data values were excluded to better enhance graphical display.

Model IV



A total of 14 data values were excluded to better enhance graphical display.

Table 17. Quantiles of Absolute Relative Prediction Error (Percentages) for Four Regression Models Considered.

Category	Sample Size	Model I				Model II			
		25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile	Mean
up to $999	33	18.05	28.39	44.80	39.70	21.76	28.98	56.54	49.44
$1,000 - $2,999	188	19.23	37.75	60.45	59.23	18.93	37.41	59.03	57.18
$3,000 - $9,999	457	24.61	45.38	69.28	71.19	22.37	43.92	66.20	67.55
$10,000 - $24,999	354	26.68	54.05	79.23	94.11	26.21	49.93	73.41	86.23
$25,999 - $49,999	155	31.45	53.22	84.99	121.40	26.81	52.43	85.52	114.11
$50,000 and above	156	31.20	58.41	95.84	148.67	28.53	60.46	95.28	137.95

Category	Sample Size	Model III				Model IV			
		25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile	Mean
up to $999	33	19.16	28.83	49.98	40.65	22.54	29.68	54.18	47.23
$1,000 - $2,999	188	19.81	36.61	56.99	58.57	18.55	36.12	58.50	57.94
$3,000 - $9,999	457	21.82	43.39	68.31	68.31	22.23	42.11	64.49	65.95
$10,000 - $24,999	354	22.65	51.17	76.41	87.26	22.80	46.58	73.03	80.99
$25,999 - $49,999	155	31.08	52.64	83.27	117.85	27.59	52.15	92.54	114.79
$50,000 and above	156	28.73	58.87	92.58	144.00	26.37	57.19	88.90	140.44

Table 18 summarizes the results of the regression analysis. It can be observed that there is improvement with the inclusion of categorical variables, especially with FSC. From both Table 17 and Table 18, it is observed that Model IV yield the best predictive power with highest R^2 and lowest prediction error among all four models.

Table 18. Summary of Regression Analysis

Model	Equation	R^2
I	$\hat{Y}_i = X_i \exp(\hat{\beta}_0 + \hat{\beta}_1 \log X_i)$	0.2347
II	$\hat{Y}_i = X_i \exp\left(\hat{\beta}_0 + \hat{\beta}_1 \log X_i + \hat{\beta}_2 F_{5998,i} + \hat{\beta}_3 F_{1560,i} + \hat{\beta}_4 F_{1615,i} + \hat{\beta}_5 F_{1620,i} + \hat{\beta}_6 F_{1680,i} + \hat{\beta}_7 F_{6625,i} + \hat{\beta}_8 F_{5841,i}\right)$	0.2954
III	$\hat{Y}_i = X_i \exp\left(\hat{\beta}_0 + \hat{\beta}_1 \log X_i + \hat{\beta}_2 L_{E,i} + \hat{\beta}_3 L_{U,i} + \hat{\beta}_4 L_{X,i} + \hat{\beta}_5 L_{Y,i} + \hat{\beta}_6 L_{A,i} \log X_i + \hat{\beta}_7 L_{Y,i} \log X_i\right)$	0.2699
IV	$\hat{Y}_i = X_i \exp\left(\hat{\beta}_0 + \hat{\beta}_1 \log X_i + \hat{\beta}_2 F_{1560,i} + \hat{\beta}_3 L_{E,i} + \hat{\beta}_4 L_{U,i} + \hat{\beta}_5 F_{5998,i} \log X_i + \hat{\beta}_6 F_{1560,i} \log X_i + \hat{\beta}_7 F_{1650,i} \log X_i + \hat{\beta}_8 F_{1680,i} \log X_i + \hat{\beta}_9 F_{5895,i} \log X_i + \hat{\beta}_{10} L_{A,i} \log X_i + \hat{\beta}_{11} L_{U,i} \log X_i\right)$	0.3146

However the most substantial improvement is found by comparing Model II to Model I. The percentage of variance explained in the response variable increases from 23.5 percent to 29.5 percent with the addition of FSC levels as predictor variables. The practical effect of this improvement can be seen with the 240 items in the sample that belong to the FSC category “5998”. For these items, the median (50th percentile) and upper quartile (75th percentile) of absolute relative errors were 42.8 percent and 70.5 percent for Model II, compared to 47.3 percent and 114.6 percent respectively for Model I.

Figure 7 shows a scatter plot of the residuals against the predicted values for Model II. Ideally, this plot does not reveal a nonlinear pattern or evidence of unequal variances (heteroscedasticity). The scatter plot does reveal some evidence that the variance of the residuals decreases with the size of the predicted value. This pattern suggests that greater efficiency may be realized by using weighted least-squares regression, although ordinary least squares also provides unbiased estimates of the regression coefficients. The normal quantile-quantile (QQ) plot of the residuals, shown in Figure 8, indicates that the distribution of residuals deviates from normality mainly due to skewness in the left-hand tail. Despite these departures from ideal model assumptions, Model II appears to be a good fit for this analysis, and an improvement over the methodology currently in use.

The next section will consider how a change in the prediction methodology would have affected assessment of the FIRST program.

Figure 7. Plot of Residuals Versus Regression Predictions for Model II

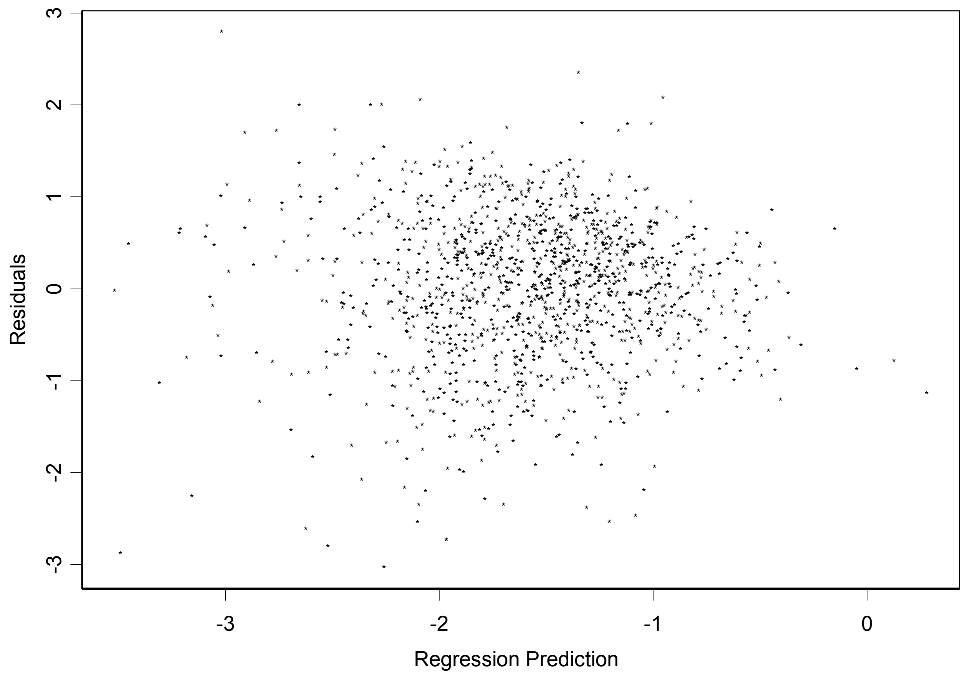
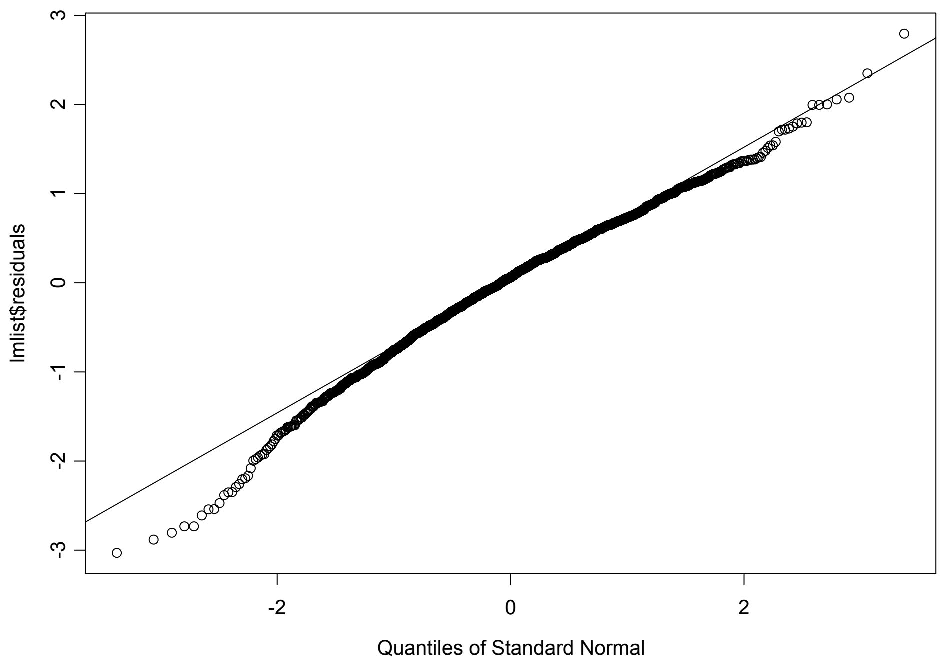


Figure 8. Quantile-normal Plot of Residuals from Model II



E. VALIDATING THE ANALYSIS WITH DATA FROM THE FIRST PROGRAM

For the FIRST Program, BCA analysis was performed by NAVICP to estimate the repair prices of its inventory items. Twenty items were reviewed in which all belongs to the last three replacement price categories (Table 19). It is observed that current NAVICP prediction methodology has the tendency to overestimate repair prices especially in this category, whereby these prediction errors had the greatest fiscal impact. Details of the estimated repair prices using NAVICP’s BCA analysis are shown in Table 20.

DoD IG report claimed that NAVICP’s BCA repair prices overstated the actual repair price [1].

Table 19. Category listings and sample size of the repair items reviewed by DoD IG

Category	Sample Size
$10,000 - $24,999	3
$25,999 - $49,999	5
$50,000 and above	12

Table 21 shows the analysis performed using the current, modified and regression method as discussed in previous section to determine the predictive power of the respective models. Comparing current prediction method adopted by NAVICP ($65.5 million) to the proposed regression method ($35.8 million), the overstatement of benefit from the PBL that DoD IG claims would have been reduced by $29.7 million. This shows that the relationship of the repair prices to replacement prices is indeed non-linear. Hence using the regression method would reduce the prediction error of repair prices by almost $30 million.

Table 20. Analysis of NAVICP BCA repair prices (FIRST Program)

FSC	NIIN	5 Yr Demand	Repair Prices	Total Cost
1430	014553659	164	$13,303	$2,181,651
1620	014636970	109	$8,115	$884,573
1620	014668717	77	$41,987	$3,232,972
1630	014551442	176	$7,970	$1,402,794
1650	014552590	123	$9,130	$1,123,039
1650	014553668	200	$7,704	$1,540,846
1650	014554490	514	$20,850	$10,716,900
1650	014691468	217	$15,339	$3,328,498
1680	014552537	469	$5,001	$2,345,375
1680	014774914	362	$55,121	$19,953,784
1680	014782049	105	$8,722	$915,810
1680	014800498	59	$38,632	$2,279,289
1720	014551420	219	$3,990	$873,786
2520	014726137	66	$28,763	$1,898,325
4320	014545082	39	$14,664	$571,896
4320	014552588	199	$7,834	$1,558,892
5998	012960824	141	$3,622	$510,646
5998	014658626	532	$5,118	$2,723,031
6115	014553692	104	$38,484	$4,002,336
6615	014820902	157	$22,606	$3,549,079

Table 21. Comparison of Predicted Repair Prices between Current, Modified and Regression Method (Model II).

Prediction Method	Total Predicted Repair Price	Total Actual Repair Price	Difference	Percent
Prediction using NAVICP BCA in IGDOD Report	$65.6 million	$21.4 million	$44.2 million	206
Prediction using Current Prediction Method	$68.9 million	$21.4 million	$47.5 million	222
Prediction using Modified Ratio Method	$55.8 million	$21.4 million	$34.4 million	161
Prediction using Regression Method (Model II)	$35.9 million	$21.4 million	$14.5 million	67

Note: Analysis is based on the 20 items identified in DoD IG report [1].

F. VALIDATING ANALYSES WITH NEWLY PROVISIONED ITEMS FOR FY 2002

In addition to validating the regression methodology with the repair-price data from the FIRST program, an analysis was also conducted with newly-provisioned items for FY 2002. After using the filtering techniques discussed in Chapter III, there were a total of 575 newly provisioned inventory items for FY 2002 that were available for analysis.

Table 22 summarizes absolute relative prediction errors for the current, modified and regression prediction (Model II) methodologies. There is no clear pattern that suggests that one methodology outperforms the others across all categories of items. It is of interest to note that, in the highest-cost category, the regression method produces the largest median of absolute relative prediction errors, but also the smallest 75th percentile of these same quantities.

Table 22. Quantiles of Absolute Relative Prediction Errors (Percentages) Using the Current, Modified and Regression Method (Model II) for Newly Provisioned FY 2002 Inventory Items.

Category	Sample Size	Current Ratio Method				Modified Ratio Method				Regression Method (Model II)			
		25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile	Mean
up to $999	32	26.91	48.34	86.10	64.15	23.66	44.54	82.61	61.06	32.20	46.58	87.89	98.18
$1,000 - $2,999	71	26.60	48.69	79.34	90.23	24.86	49.71	79.75	87.99	23.07	40.63	76.15	62.95
$3,000 - $9,999	173	17.02	35.77	78.77	82.39	18.07	37.19	73.55	78.14	20.28	42.88	72.63	63.03
$10,000 - $24,999	128	18.88	44.95	73.71	75.95	19.63	44.83	72.10	75.04	26.50	50.30	77.37	80.90
$25,999 - $49,999	54	40.49	61.81	116.64	104.68	39.83	62.75	119.02	105.87	22.62	49.09	72.89	68.29
$50,000 and above	117	6.69	42.11	89.90	162.42	17.35	35.98	72.06	128.51	22.75	42.19	72.77	68.76

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V. CONCLUSIONG AND RECOMMENDATIONS

A. INTRODUCTION

The intention of this research is to develop a predictive model for estimation of repair prices. This research was initiated after DoD IG instigated a review of the FIRST Program awarded to Boeing whereby the Navy largely underestimated the repair prices. It was observed that of the 20 inventory items reviewed by DoD IG, twelve are from the highest price category as shown in Table 19.

B. CONCLUSION AND RECOMMENDATIONS

In this research, three methodologies were considered. The first, a modified ratio methodology, is somewhat similar to the current ratio methodology used by NAVICP. The second is based on a regression with logarithmic transformations of both the response and predictor variables, and the third is an extension which includes categorical variables in regression analyses.

It is observed that the largest share of the overall prediction error occurs with items having the largest replacement prices ($10,000 and above). But, in the highest cost category, there is noticeable improvement if the modified ratio methodology is used. Using the modified ratio methodology, the difference between predicted and actual repair prices was reduced to approximately $34 million. However, this error is still large in light of

the fact that the actual repair price of the items considered was only $21 million. This finding suggests that there may have been much to be gained by examining alternative prediction methodologies.

One suggestion highlighted in this research is the use of transformed regression analysis. As shown in Figure 5, the relationship of replacement to repair price is fairly well correlated on a logarithmic scale. Additional analysis using categorical variable are also presented in Chapter IV.

Box plots for the regression methods, as shown in Figure 6, all indicates improvement in the higher price category, especially model IV (i.e. regression analysis with both FSC and LRC as categorical variable) which yield the best results. However it can be noted that all regression methodology though performed fairly well, had hardly any vast distinctive improvement among each other, even with the inclusion of categorical variables. Thus it seems that analysis with regression methodology should suffice for the estimation of repair prices.

Similarly, the predictive ability of the regression method is tested with the repair items reviewed by DoD IG [1]. This model presented significant improvement in the predictive ability and the prediction error drops from an observed $47 million (using current ratio method) to about $14 million.

It is recommended that NAVICP consider the use of regression analysis with logarithmic transformations to develop it repair matrix. These models are able to incorporate predictors other than the replacement price, including FSC and LRC, which were found to be of some value. With a concerted research effort it is possible that other effective predictors may also be found.

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APPENDIX A: LISTING OF FSC AND LRC GROUPING WITH DESCRIPTION

FSC Code and Description

1210-1290 Fire Control Equipment
1305-1398 Ammunition and Explosives
1410-1450 Guided Missiles
1560-1560 Aircraft Airframe Structural Components
1610-1615 Aircraft Propellers and Helo Rotor Blades & Drive Mechanisms
1620-1680 Aircraft Components and Accessories
1710-1990 Aircraft Launch Land & Ground Service Equip
2010-2090 Ship & Marine Equipment
2210-2350 Railway Equipment
2410-2430 Tractors
2510-2590 Vehicular Equipment Components
2610-2640 Tires and Tubes
2805-2895 Engines Turbines & Components
2910-2995 Engine Accessories
3010-3040 Mechanical Power Transmission Equipment
3110-3130 Bearings
3210-3230 Woodworking Machinery & Equipment
3405-3470 Metalworking Machinery
3510-3590 Service And Trade Equipment
3605-3695 Special Industry Machinery
3710-3770 Agricultural Machinery & Equipment
3805-3895 Construction, Mining, & Excavating
3910-3990 Materials Handling Equipment
4010-4030 Rope, Cable, Chain, & Fittings
4110-4140 Refrigeration & Air Conditioning
4210-4240 Fire Fighting, Rescue & Safety Equipment
4310-4330 Pumps and Compressors
4410-4470 Furnace, Steam Plant & Drying Equipment
4510-4540 Plumbing, Heating & Sanitation Equipment
4610-4630 Water Purification/Sewage Treatment Equipment
4710-4730 Pipe, Tubing, Hose, & Fittings
4810-4820 Valves
4910-4960 Maintenance & Repair Shop Equipment
5110-5180 Hand Tools
5210-5280 Measuring Tools
5305-5365 Hardware and Abrasives
5410-5450 Prefabricated Structures & Scaffolding

FSC Code and Description
5510-5530 Lumber, Millwork, Plywood & Veneer
5610-5680 Construction & Building Materials
5805-5895 Communication & Detection Equipment
5905-5999 Electrical & Electronic Equipment Components
6010-6080 Fiber Optics Materials & Components
6105-6150 Electric Wire, Power & Distribution Equipment
6210-6260 Lighting Fixtures and Lamps
6310-6350 Alarm, Signal & Security Detection Systems
6505-6550 Medical, Dental Equipment & Supplies
6605-6695 Instruments & Laboratory Equipment
6710-6780 Photographic Equipment
6810-6850 Chemicals & Chemical Products
6910-6940 Training Aids & Devices
7010-7050 Data Process & Support Equipment
7105-7195 Furniture
7210-7290 Household, Commercial Furnishings& Appliances
7310-7360 Food Preparation & Serving Equipment
7420-7490 Office Machines, Text Proc Equip & Visible Record Equipment
7510-7540 Office Supplies & Devices
7610-7690 Books, Maps & Other Publications
7710-7740 Musical, Phonographs & Home-Type Radios
7810-7830 Recreational & Athletic Equipment
7910-7930 Cleaning Equipment & Supplies
8010-8040 Brushes, Paints, Sealers & Adhesives
8105-8145 Containers, Packaging, & Packing Supplies
8305-8345 Textiles, Apparel, Shoe Findings-Tents&Flags
8405-8475 Clothing, Individual Equipment & Insignia
8510-8540 Toiletries
8710-8730 Agricultural Supplies
8810-8820 Live Animals
8900-8999 Subsistence-Food
9110-9160 Fuels, Lubricants, Oils & Waxes
9310-9390 Nonmetallic Fabricated Materials
9410-9450 Nonmetallic Crude Materials
9505-9545 Metal Bars, Sheets, and Shapes
9610-9680 Ores, Minerals & Their Primary Products
9905-9999 Miscellaneous

LRC Code and Platform

A	F/A-18 A/D
B	F/A-18 E/F
C	AV-8B
D	EA-6B
E	F-14
G	V-22
H	S-3
J	C-130,E-6,F-5,F-16,T-38
L	P-3
M	E-2
P	C-2
Q	Common Systems
R	T-45
S	Aircraft Engines
T/U	Aviation Support Systems
V	H-1/H-46
X	H-3/H-53
Y	H-60

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